Extraction of Compton Form Factors from DVCS Data

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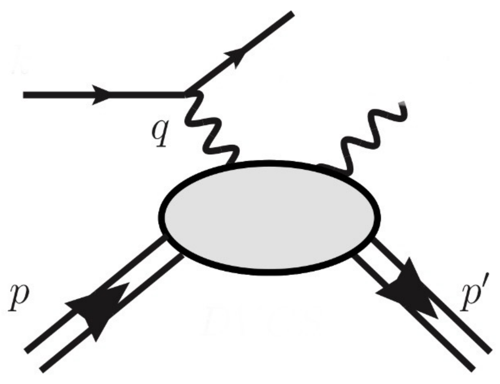
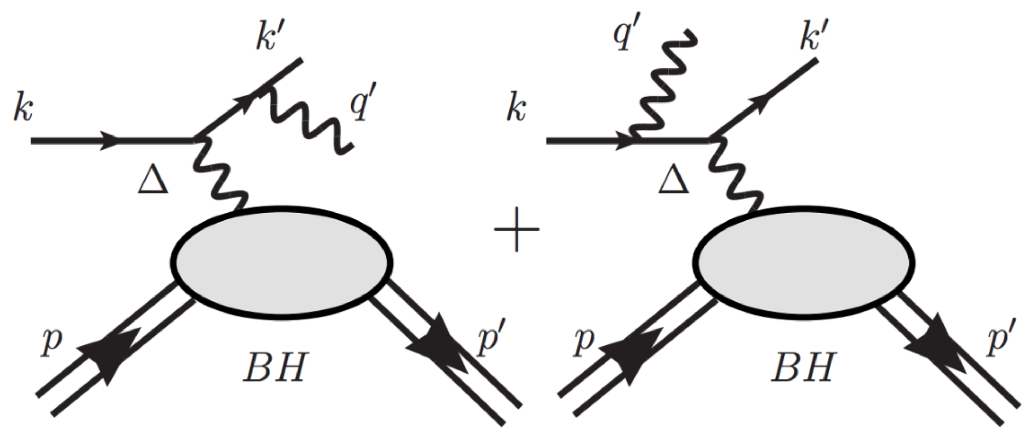
I. DVCS



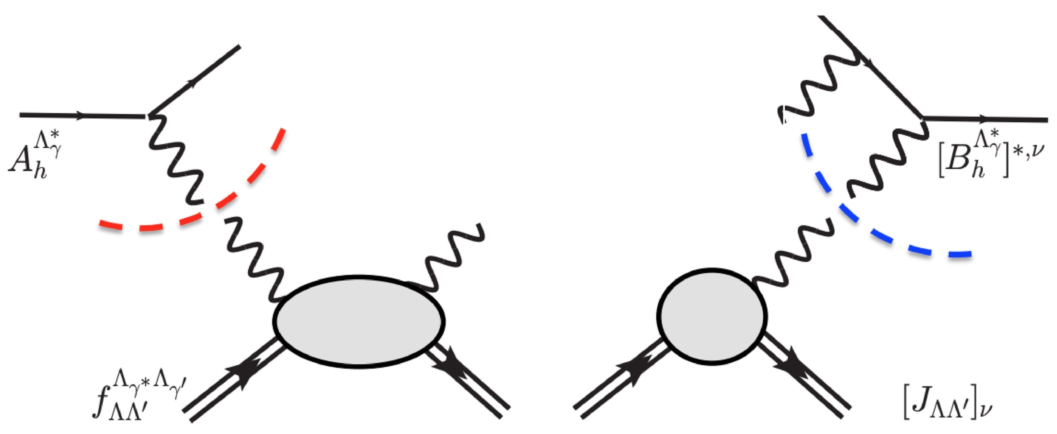
Deeply Virtual Compton Scattering (DVCS) is described by the process

$$\gamma^*(q) + p \rightarrow \gamma'(q') + p',$$

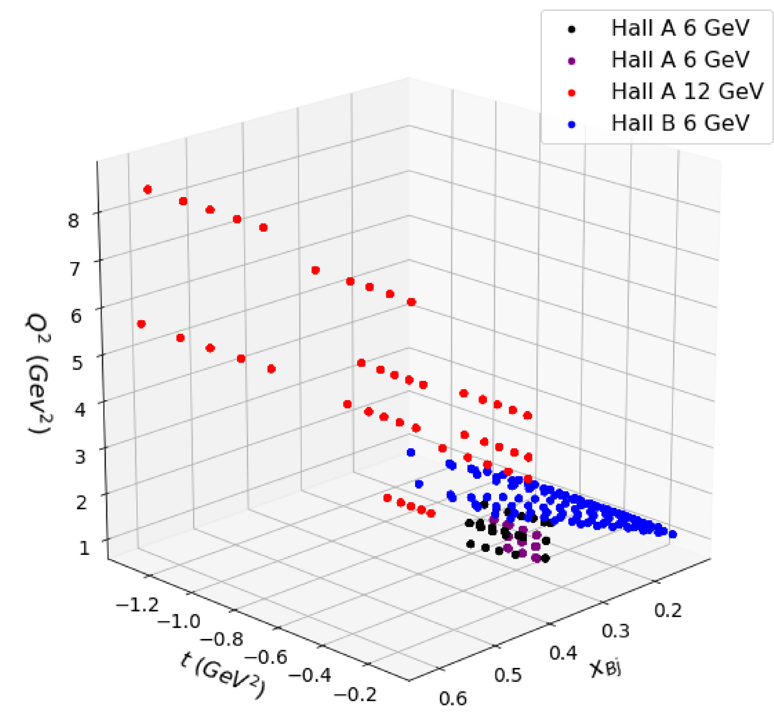
The background process is Bethe Heitler (BH)



There is an interference term in the total cross section from which we extract Compton Form Factors using Rosenbluth separation techniques.

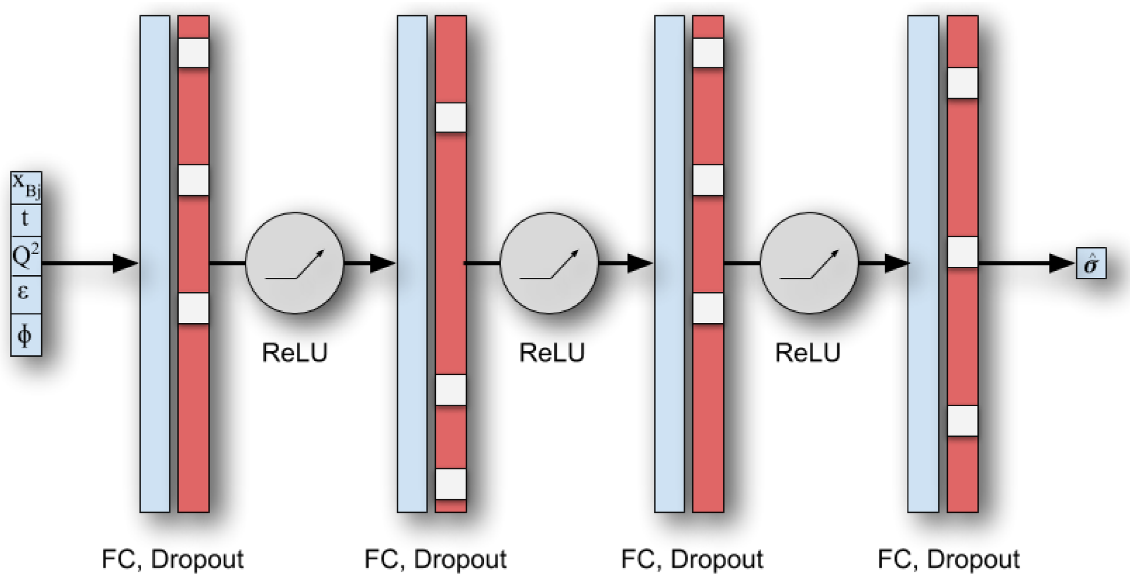


Total JLab data that we are using in our analysis



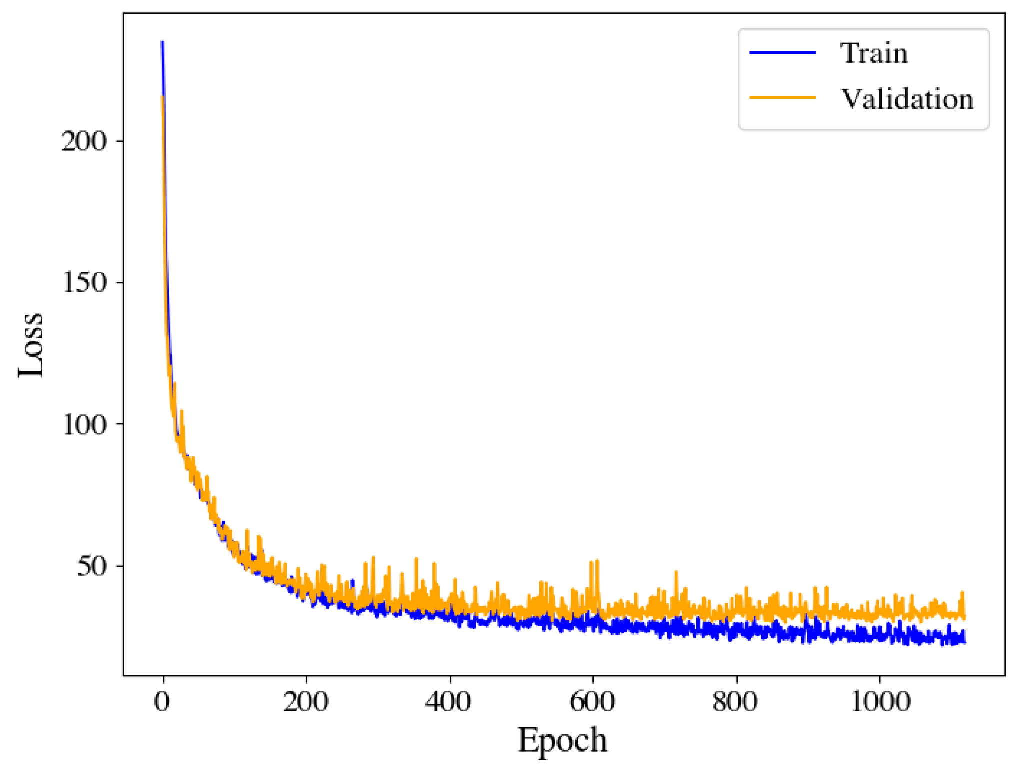
II. Training a Cross Section Network

We build a model that learns to predict σ_{UU} or σ_{LU} [2] for a given kinematic bin $\mathbf{x} = (x_{Bj}, t, Q^2, \epsilon, \phi)$. The model is a multilayered perceptron (MLP) with 4 hidden layers, each followed by a rectified linear unit (ReLU) activation function. In addition, we use Dropout [3] layers to encourage the network to learn robust representations. We minimize the *huber loss* of the the model's predictions w.r.t its parameters θ:



$$\mathcal{L}_\theta(\mathbf{x}, \sigma) = \begin{cases} \frac{1}{2}(\sigma - f_\theta(\mathbf{x}))^2, & \text{if } |\sigma - f_\theta(\mathbf{x})| \le 1; \\ \frac{1}{2}|\sigma - f_\theta(\mathbf{x})|, & \text{if } |\sigma - f_\theta(\mathbf{x})| > 1; \end{cases}$$

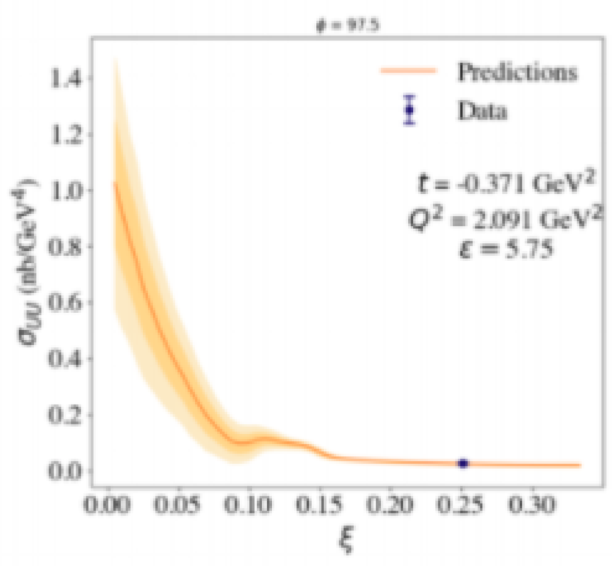
This lets us fit the cross section on many different orders of magnitude. We use the Adam optimizer to terminate training when the error stops improving on a held-out validation set.

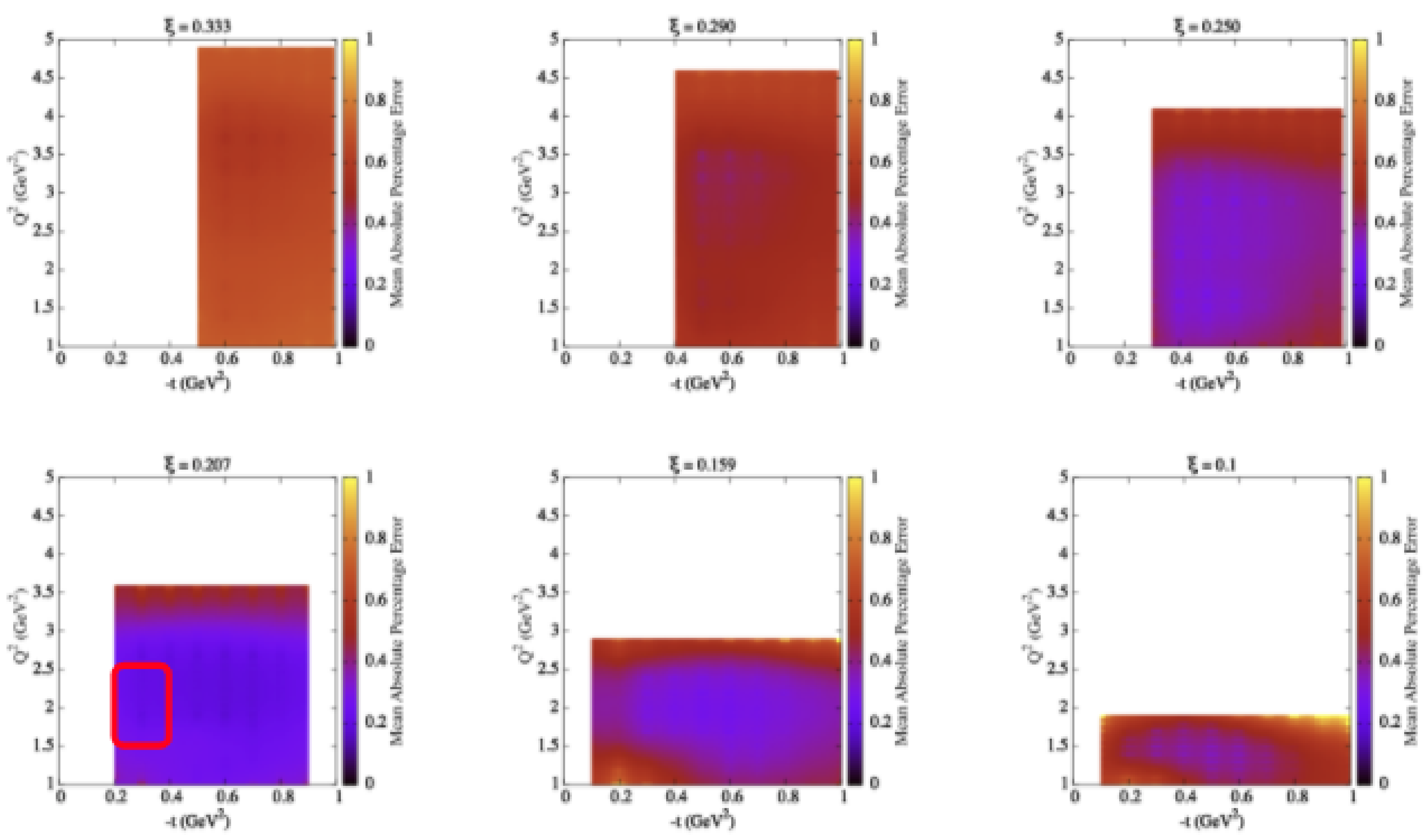


III. Cross Section Predictions

We estimate model uncertainty as in [1]. Dropout is left on during inference, so that each prediction can be seen as a sample from the set of possible sub-networks of the fully trained architecture.

We can use the model to sweep through kinematic regions where data does not exist. We compare with theoretical calculations and see that we can predict certain phase space regions away from the data (red rectangle).





The model and software will be released and updated as new experimental data are published.

IV. Rosenbluth Separation

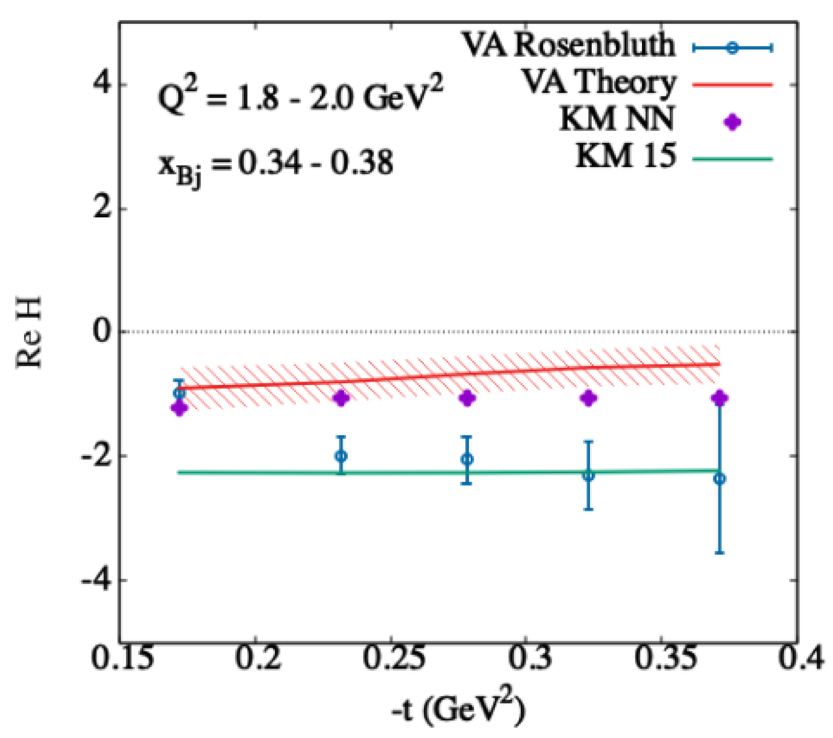
We exploit the linear dependence in Compton Form Factors of the interference cross section

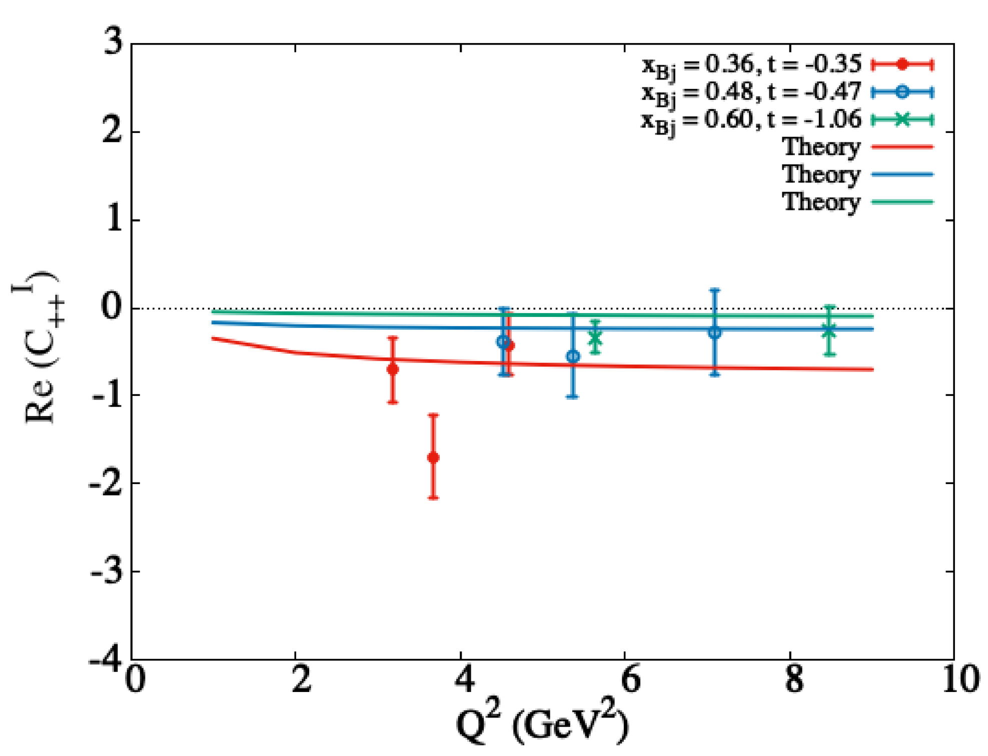
$$\sigma^{\mathcal{I}}_{UU} = A^{\mathcal{I}}_{UU}\Re e(F_1 H + \tau F_2 E) + B^{\mathcal{I}}_{UU}\Re e G_M(H+E) + C^{\mathcal{I}}_{UU}\Re e G_M \widetilde{H}$$

to independently extract the Re and Im parts of H and E by using a generalization of the Rosenbluth separation technique.

$$\frac{\sigma^{\mathcal{I}}_{UU}}{B^{\mathcal{I}}_{UU}} = \frac{A^{\mathcal{I}}_{UU}}{B^{\mathcal{I}}_{UU}}\Re e(F_1 H + \tau F_2 E) + \Re e G_M(H+E)$$

where we treat the contribution of $(C^{\mathcal{I}}_{UU}/B^{\mathcal{I}}_{UU}) G_M \widetilde{H}$ as small.





References

[1] Y. Gal and Z. Ghahramani. Dropout as a bayesian approximation: Representing model uncertainty in deep learning. 2016.

[2] B. Kriesten, S. Liuti, L. Calero-Diaz, D. Keller, A. Meyer, G. R. Goldstein, and J. Osvaldo Gonzalez-Hernandez. Extraction of Generalized Parton Distribution Observables from Deeply Virtual Electron Proton Scattering Experiments. *Phys. Rev. D*, 101(5):054021, 2020.

[3] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. 2014.

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